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Extraction of characteristics for data-informed guidance and counseling using trace data

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Abstract

Guidance and Counseling (G&C) in schools is a crucial activity that helps learners acquire academic knowledge and skills while fostering comprehensive psychological and social development. The digitization of the educational environment means that trace data related to students' learning and lives are being accumulated; it is expected that integrating this with other data sources will enable teachers to better understand learners and enhance G&C strategies. However, the utilization of trace data for G&C has not been examined. One of the reasons is the difficulty of interpreting granular data without considering the subject characteristics and activity contexts. Therefore, to enable homeroom teachers to utilize trace data from a G&C perspective, this study aimed to extract characteristics from trace data to support teachers' understanding of learners in the G&C process. Based on the "Multi-Tiered Support" model adopted in G&C practice, we extracted characteristics that capture the learners' state and interviewed teachers to investigate how these characteristics can be used in actual settings. The results suggest that these characteristics would help teachers to understand learners' situations both in and outside of schools. The contribution of this study is to aggregate and standardize trace data, transforming it into a level of granularity that homeroom teachers can interpret from a G&C perspective.

Keywords: guidance and counseling, learning analytics, multi-tiered systems of support

Introduction

In 21st-century schools, teachers ensure that learners acquire academic knowledge and competencies but also help them develop character, morals, soft skills, and psychological well-being (Naraswari, 2024). This educational approach is known as Guidance and Counseling (G&C), and aims to support individuals to develop useful skills, insights, and the ability to adapt to their environments, thereby enhancing their overall functionality (Dianovi et al., 2022; Lai-Yeung, 2014; Naraswari, 2024). Although specialized staff such

as counselors or vocational teachers are sometimes responsible in some countries, homeroom teachers need to collaborate in this activity. A deep understanding of learners is fundamental to functioning G&C (MEXT, 2022). However, even for experienced teachers, understanding each learner's circumstances and addressing diverse needs presents a significant challenge because it requires considerable effort and time (MEXT, 2022). In addition, G&C involves diverse stakeholders, requiring systematic tracking and sharing of when, to whom, and how support was provided to enable informed collaboration (Gysbers & Henderson., 2012). A representative model used in G&C to address these diverse learners' needs is the *multi-tiered system of support* (MTSS), a data-driven framework aimed at improving outcomes for all learners (Ito et al., 2023; Nitz et al., 2023; Saia, 2023). MTSS relies on multiple data sources for informed decision-making, including demographic data, benchmark or diagnostic assessments, and standardized test scores (Saia, 2023). However, data collection frequency is limited, and behavioral observations tend to be subjective (Saia, 2023).

On the other hand, the use of ICT tools has been widely spread in schools in recent years. In Japan, the GIGA（Global and Innovation Gateway for All） School Program provides learners with their own devices such as tablet computers (MEXT, 2019). This has enabled the accumulation of cross-contextual data related to learners' learning history and daily life activities (Dong & Miao, 2023; Ogata et al., 2023;). These trace data indicate learners' actions in digital learning environments, enabling the tracking of their learning processes. Learning Analytics (LA) techniques have utilized these trace data to monitor learners' daily activities, make predictions and recommendations, and provide feedback (Khor & Mutthulakshmi, 2024). LA has the potential to support teachers' understanding of students and their interventions in G&C, and to track learners' behavior after the intervention.

However, despite such needs and potential, the utilization of cross-contextual trace data for G&C has not been examined, nor have strategies and frameworks to support teacher interventions been explored. One reason is the difficulty of interpreting granular data without considering the subject characteristics and activity contexts. Therefore, effective data processing is essential to support them using trace data.

Thus, this study aimed to extract the characteristics that support teachers' understanding of learners in the G&C process. We assumed that the extracted characteristics would be utilized by homeroom teachers, who often undertake G&C regardless of the specific subject matter. We communicated with actual homeroom teachers involved in G&C to investigate the activities conducted during the process and the characteristics that can be utilized to understand learners. This study begins by examining the literature, identifying gaps, and extracting G&C characteristics.

Literature Review

Theoretical Basis of Guidance and Counseling

Overview of Guidance and Counseling

Although the terms and concepts of G&C vary slightly by country (e.g., *comprehensive school guidance and counseling approach and whole school approach*), a common point is that it is an educational activity that takes place in schools (Cefai et al., 2021; Gysbers & Henderson, 2012). In some countries, no clear concept is equivalent to G&C, and activities such as *social and emotional learning* (SEL) may serve similar purposes (Suzuki, 2021).

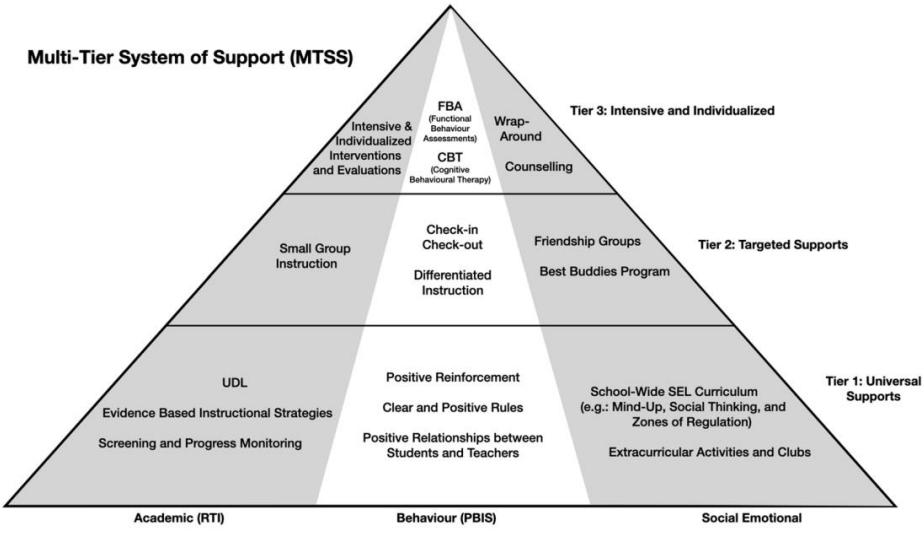
Teachers require a deep understanding of their learners to enhance G&C activities (MEXT, 2022). In this process, it is necessary to grasp each student's needs and interests, as well as the home environment, upbringing, capabilities, aptitudes, and interests (MEXT, 2022). This will facilitate the provision of subsequent support and intervention such as *positive behavior intervention and support* (PBIS), addressing difficult issues, and problem prevention (Cressey, 2019; MEXT, 2022). Additionally, G&C is based on insights from developmental science (including developmental psychology), which emphasizes the importance of understanding individual growth and change, and behavioral science, which focuses on the modifying of observable behaviors (Cressey, 2019; Fisher & Lerner, 2005; Geidner, 2009). In other words, G&C requires teachers to understand learners' diverse needs based on these developmental and behavioral science perspectives and provide interventions tailored to developmental stages to facilitate changes in observable behaviors. However, addressing the diverse needs of learners can be challenging, as inexperienced teachers might overlook these changes, and even experienced teachers must invest significant time and effort to understand learners' states and progress (MEXT, 2022; Wolff et al., 2016).

Existing Model: Multi-Tiered Systems of Support (MTSS)

G&C is divided into several phases in many countries to meet these learners' diverse needs (Myrick, 1987). The representative model is called the *multi-tiered system of support* (MTSS) (Ito et al., 2023; Nitz et al., 2023). Historically, it was formed by integrating the *response to intervention* (RTI) and *school-wide positive behavior support* (SWPBS) models, and functions as a foundation for providing learning support that utilizes evidence-based educational practices (Berkeley et al., 2020). The MTSS is a preventive, data-based framework for addressing diverse needs and improving student outcomes (Miller et al., 2014). The MTSS consists of three levels, called tiers, and three domains: behavioral, academic, and social-emotional. Through this model, the supports and interventions in

G&C are designed to meet the different needs of each student. The model is represented as a triangle, illustrating the increasing complexity of the challenges in G&C and the number of students to be served (Figure. 1).

Figure 1
Structure of multi-tiers systems of support (MTSS)
(Ito et al., (2023) Adapted from Center on Positive Behavioral Interventions and Supports (2020), R.T.I. Action Network (2020), Sailor et al. (2021), and The Collaborative for Academic, Social, and Emotional Learning (2020).)



Tier 1 includes daily school activities, universal design, and support for all learners. Tier 2 focuses on the early detection and prevention of challenges for some learners. Tier 3 provides individualized and intensive interventions for specific difficulties. Lower tiers involve routine tasks for all learners, whereas higher tiers focus on targeted support for a few. The MTSS model categorizes interventions into three tiers— across academics (RTI), behavior (PBIS), and social-emotional learning (SEL), with strategies tailored by tier.

However, MTSS requires the collection of multiple data sources for use in decision-making (Saia, 2023). This includes, but is not limited to, demographic or categorical data, benchmark or diagnostic assessment data, and standardized test scores (Saia, 2023; Nitz et al., 2023). In addition, depending on the type of data, it may only be feasible to conduct it as a periodic psychological test, often on an annual or semester basis, resulting in low acquisition frequency. This is partly because such tests can be psychologically invasive and therefore are not suitable for frequent administration. Consequently, there is a tendency to rely on subjective behavioral observations instead (Nitz et al., 2023; Miller et al., 2014).

Technology-enhanced Guidance and Counseling

Guidance and Counseling using Learning Analytics (LA) Technology

The digitization of the educational environment has led to the accumulation of learning logs and the use of data through Learning Analytics (LA) technology. LA is described as "the collection, analysis, interpretation and communication of data about learners and their learning that provides theoretically relevant and actionable insights to enhance learning and teaching." (Society for Learning Analytics Research, 2025). LA uses log data from e-learning, LMS, computers, and tablets—including learning records, quiz responses, page views, and activity frequency—and provides monitoring, assessment, and analysis, thereby enabling personalized learning (Agus & Samuri, 2018; Khor & Mutthulakshmi, 2024). This makes it possible to identify the learning progress, level of understanding, and areas of weakness for each subject, and to optimize learning support for individual learners. Studies have also been conducted to prevent dropouts through at-risk detection (Oliveira, 2021). In this sense, LA contributed to understanding the learners' situations from the data.

Although extensive research has been conducted in diverse areas, few studies have explored the application of LA in broader G&C contexts. In subject areas such as language and mathematics, granular information such as learners' actions, page transitions, and performance data can support subject teachers' instructional decisions even when presented as raw values because it indicates whether actions align with the teacher's intent and whether learners are progressing toward the target. In contrast, G&C involves homeroom teachers who manage the classroom and support learners. It is difficult for them to interpret such detailed data without considering the subject characteristics and activity contexts. In other words, when LA provides information that captures the learners' daily efforts, behaviors, and socio-emotional challenges, it can be a valuable resource for G&C.

Research Position and Novelty

This study was positioned at the intersection of the LA and G&C processes. Previous studies have highlighted the following gaps:

- Reliance on subjective and infrequently obtained data in G&C.
- Lack of technology to interpret trace data beyond the specific context.

Therefore, to enable homeroom teachers to utilize trace data from a G&C perspective, this study aimed to extract characteristics from trace data to support teachers' understanding of learners in the G&C process. Based on the MTSS adopted in G&C practice, we extracted the characteristics that captured the learners' states and interviewed teachers to investigate how these characteristics could be used in classroom settings.

Accordingly, the following Research Questions have been established.

- RQ1: What G&C characteristics can be extracted from trace data?

- RQ2: How do teachers evaluate and provide feedback on the extracted characteristics?

Analysis and Methodology

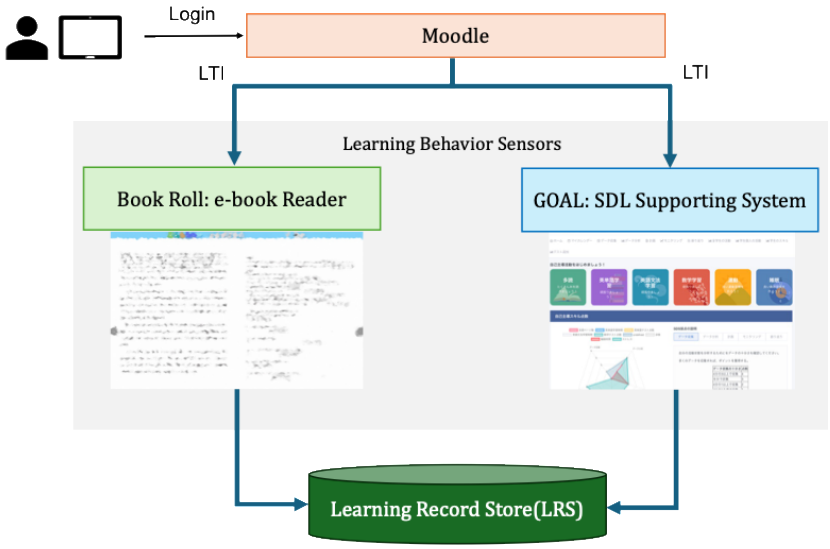
This section outlines the environment and the methods employed for the analysis.

Overview

This study collected data from a Japanese junior high school that had been using the *learning analytics and evidence framework* (LEAF) (Ogata et al., 2023) for more than three years in their daily learning activities. Figure 2 shows the architecture of LEAF, which is a digital learning environment consisting of Moodle, a learning management system (LMS), multiple activity sensors, and a Learning Record Store (LRS).

Figure 2

Structure of learning and evidence analytics framework (LEAF)



From Moodle, learners can access the learning behavior sensors, BookRoll (Ogata et al., 2023), and a *goal-oriented active learner* (GOAL) system (Li et al., 2021). Learners can engage in various learning activities within this system using the tablet computers provided by the GIGA School Program (Ogata et al., 2023). LEAF is not part of the LMS but rather interacts with it through LTI. The trace data used in LEAF adheres to a global standard called Experience API (xAPI), allowing it to be seamlessly integrated with logs from other learning tools following the xAPI standard.

Data Context

This study used the log data of daily activities in the GOAL system to answer RQ2. The GOAL system was designed to support the self-directed learning (SDL) process by guiding

learners through a structured model called DAPER (Majumdar et al., 2019). By following the DAPER model, the GOAL system aims to make SDL more systematic and effective. This approach synthesizes personal health and learning logs from multiple sources and presents them to learners (Majumdar et al., 2019), allowing them to see the goals they have set for themselves, activity indicators, and scores. Learners' SDL includes learning and physical activities. The learners recorded their weekly math test scores using this system. In addition, data such as daily steps taken and sleep duration, collected by the GARMIN device (wearable watch), were also linked to the system. Furthermore, GOAL aggregates the activity times within BookRoll.

We used five datasets: math activity time, English activity time, math score, stress level, and the number of steps taken. These indicators were selected not only based on their availability, but also because they possess characteristics that span the three domains of MTSS. For example, activity time and test scores are academic indicators that reflect behavioral and social-emotional domains, such as persistence, motivation, and self-efficacy, which have been shown to play a key role in academic achievement (Basileo et al., 2024). Stress levels correlate with not only the social-emotional domain but also with academic and behavioral challenges like poor concentration and memory (Pathak, 2025), and steps taken are associated with improved concentration (Committee on Physical Activity and Physical Education in the School Environment et al., 2013).

This math score is based on the scores from weekly math quizzes based on regular homework assignments, whereas English scores were not included because of the absence of activity. The data gathered from 200 learners covered the period from June 2020, when the students were enrolled (the start was two months later than usual due to COVID-19), to March 2023, when they graduated from school. Table 1 presents an example of a learning log.

Table 1

Examples of learning log data recorded by GOAL

User_id	Type_id	Day	Full_value	Value	Create_time
S001	107	2024/12/11	32	32	2024/12/11 9:36
S001	118	2024/12/12	Nan	25.5	2024/12/12 10:11
S001	201	2024/12/12	Nan	6.6	2024/12/14 0:04

The "type_id" represents the type of activity, such as Math score, English activity time, sleep duration time, and steps taken. This "value" represents the original value of each indicator. The activity time was recorded in minutes, and the scores reflected the actual score. Additionally, the "Full_value" column indicates the maximum possible score when a full score is defined, such as test scores.

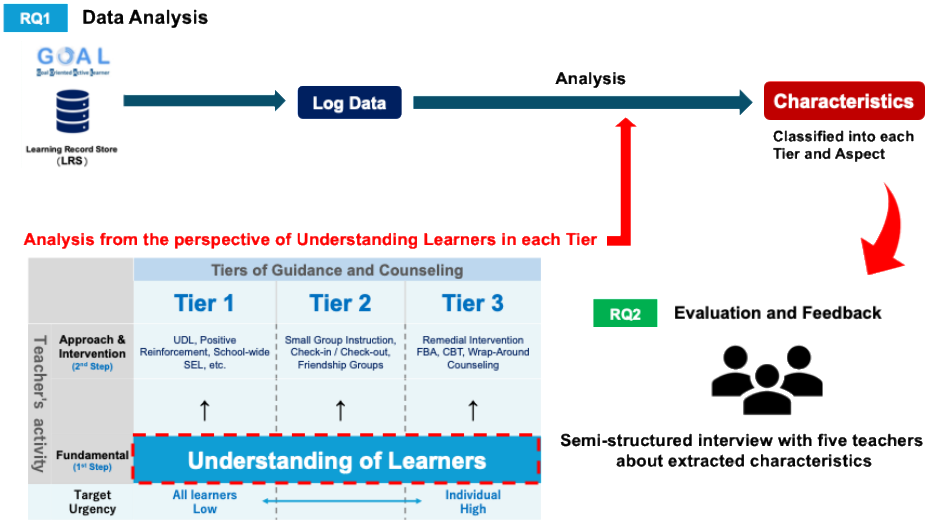
The Analysis Procedure

We defined important characteristics of G&C through a literature review and interviews with homeroom teachers in Japanese junior high schools to determine what changes and signs they focus on when assessing a learner's status. Based on this analysis, we identified the characteristics that can be extracted for G&C.

We conducted a needs analysis by interviewing two teachers to clarify the types of log data that would be useful for G&C (RQ1). Next, based on the needs analysis and literature review, we analyzed the log data and extracted the characteristics (RQ2). Finally, we conducted semi-structured interviews with five teachers to collect their evaluations, feedback, and expectations regarding the extracted characteristics (RQ3). The sequence of the analytical flow is shown in Figure 3.

Figure 3

The procedure of analysis



Data Processing

We attempted to integrate and scale various log data with different contexts in the GOAL system because the meanings of these numbers vary by context. English and math activity times represent the time used for independent study, which is an indicator of engagement—learners' high or low interest in learning. Math scores are the learning scores for tasks assigned by the teacher. For example, the activity time values were recorded in minutes per activity, whereas scores were recorded against the maximum score. The number of steps taken per day was also recorded. Stress levels were recorded from 0 to 100, with values closer to 0 indicating lower stress levels and values closer to 100 indicating higher stress

levels. The GARMIN device classifies stress into four levels: 0–25, rest; 25–50, low; 51–75, middle; and 76–100 high.

Therefore, the meanings of these values differ according to the context. Hence, we represented these different values on a 10-point scale using the following method: values closer to 10 represent learners' good state, and values closer to 0 represent a critical state (Figure 4).

For example, because the activity time depends on the overall distribution, we performed logarithmic transformation rounding for outliers, followed by normalization. Because normalization takes a distribution from 0 to 1, the value multiplied by 10 was used as the value after scaling.

The score was expressed as a percentage of the full score on a 10-point scale. Next, because the math score values had maximum values, they were converted so that the score percentage of the full score could be expressed on a scale of 10. The number of steps was then scaled based on previous studies that examined the associations between steps and adolescent health (Tudor-Locke et al., 2011; Weres et al., 2022) —that is, 10 for more than 12,000 steps per day, from 5.1 to 9.9 for between 10,000 and 12,000 steps per day, from 2.5 to 5 for 6,000 to 10,000 steps, and below 2.5 for less than 6,000 steps. Finally, the stress levels were calculated. The original value was determined using the GARMIN device, which uses heart rate variability. The original scale uses 0 for a low-stress level and 100 for a high-stress level, where multiplying by 0.1 would have the opposite meaning. Therefore, we subtracted 100 from the recorded value, took the absolute value, and multiplied it by 0.1. In addition, the four pre-defined stress levels were used to interpret the scaled values: 10 to 7.6 = very good, 7.5 to 5.1 = good, 5.0 to 2.5 = medium, and 2.5 to 0 = critical. The scaling of these datasets resulted in the following distribution (Figure 5).

Figure 4

Scaling logic and scores

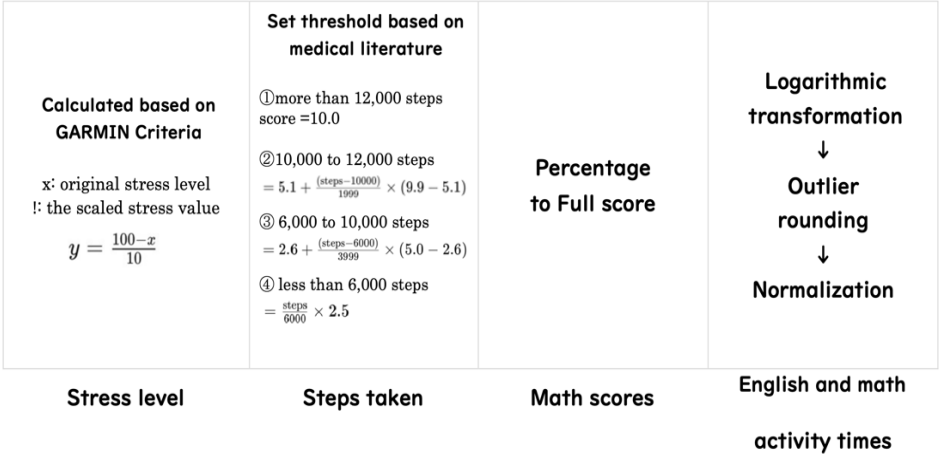
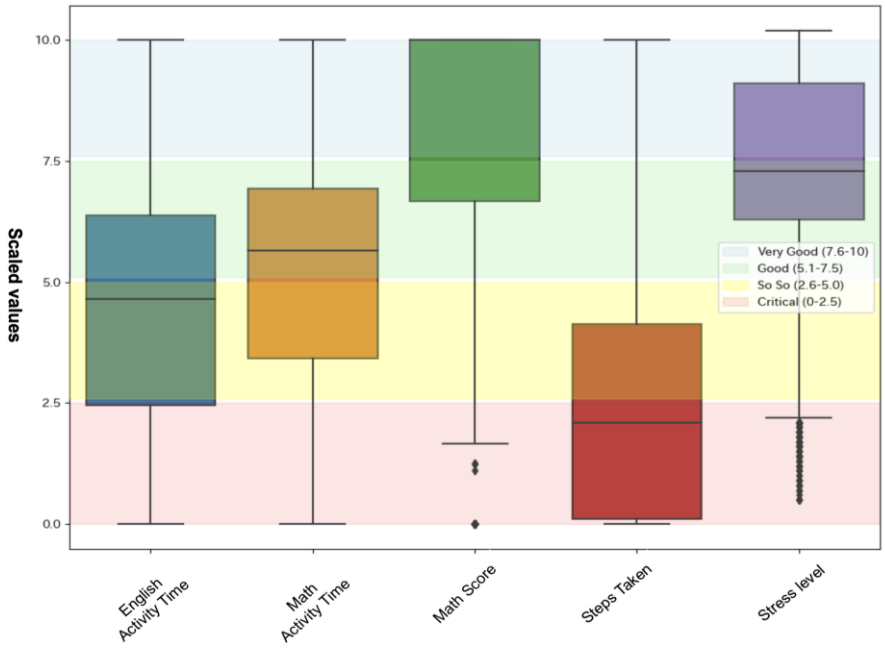


Figure 5

Box plot of scaled scores for each context



Interview Design and Analysis

Semi-structured interviews were conducted to collect evaluations and feedback on the extracted characteristics. The interviewees were five teachers at a junior high school in Japan who used this system in daily practice, and the interview consisted of three questions. The number of respondents varied by question, with two teachers participating in question 1 (Q1) and 2 (Q2), and five in question 3 (Q3). For Q1 and Q2, we interviewed the supervisor of G&C and the head teacher of protective custody to obtain a preliminary evaluation of the extracted characteristics. For Q3, we interviewed three homeroom teachers, in addition to the two teachers interviewed earlier, to examine whether these characteristics could be practically applied by homeroom teachers in the MTSS model. The specific questions were as follows:

- Q1: What changes are you likely to detect in your learners when the values of these five indicators change (increase or decrease)?
- Q2: How do you think you can use these characteristics in G&C as homeroom teachers?
- Q3: How do you think this visualization of the characteristics will help you understand which domains of the Multi-Tiered Support model?

For Q1 and Q2, the teachers responded to a multiple-choice question based on MEXT's (2022) G&C practice and then explained the reasons for their selections; only these

explanations were treated as qualitative data and coded. For Q3, teachers classified each characteristic as “Useful,” “Not useful,” or “Unclear” to the MTSS model and explained their reasoning; these utterances were also coded. The coding focused on three aspects: (1) subjects of teachers’ awareness, (2) situations of use, and (3) teachers’ concerns and perceived limitations.

Result

RQ1. Extraction characteristics from trace data

Polar charts were used to visualize the status of learners in different contexts, representing all the scaled learner values (Figure 6). This also reflects the learner’s status. An example of this visualization is shown in Figure 7.

Figure 6

Example list of learner state visualizations across learning and daily life domains

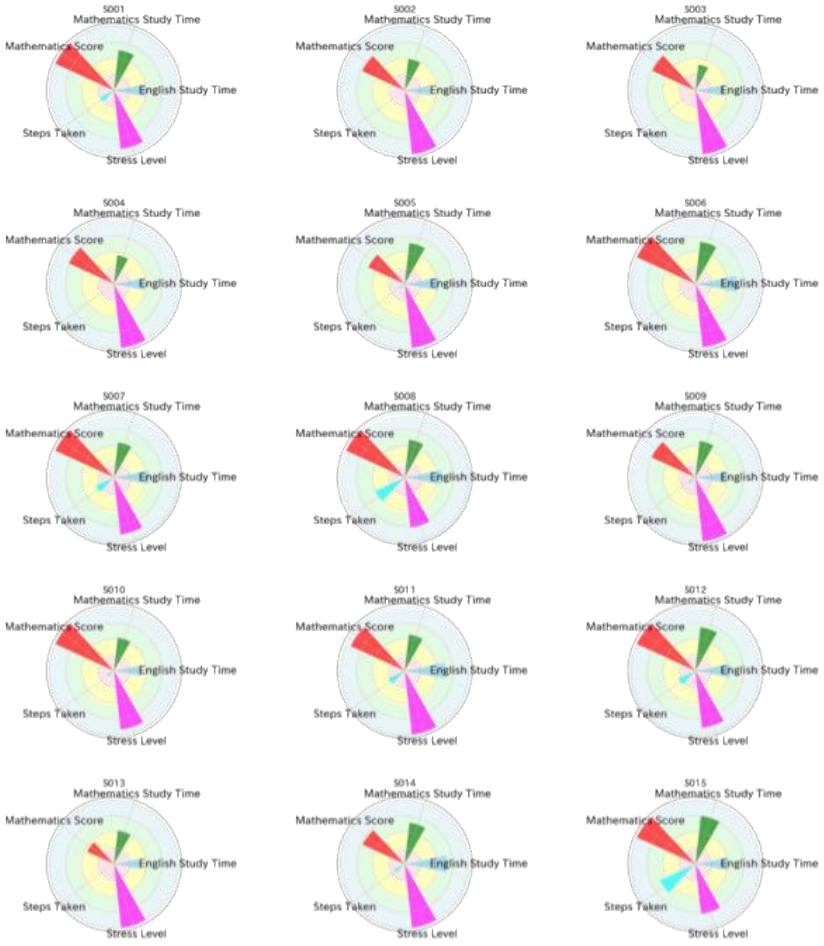
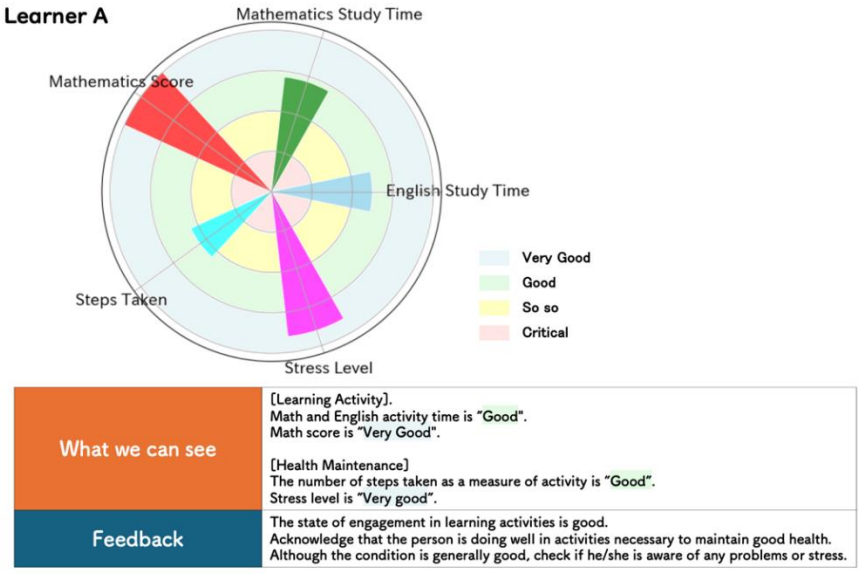


Figure 7

Visualization of sample learner A



To answer the second research question, we analyzed GOAL system trace data to identify key indicators that reflected the learner's current state. The following key indicators and characteristics emerged from the data visualization.

The first was the time and score of the learning activities. These indicators reflect learners' engagement within and achievement of educational tasks. Using these indicators, high engagement and good scores indicate positive engagement and learning attitudes, whereas low engagement and low scores may indicate potential problems, such as a lack of interest or understanding, which are important for student understanding.

The second was the number of steps taken. This indicator serves as a measure of physical activity and is important for maintaining health. Using this indicator, the maintenance of a constant number of steps is indicative of health, physical condition, and mental health, whereas a low number of steps may indicate potential health problems or low motivation, which are characteristics used to understand learners.

Finally, stress levels were considered. Stress levels are directly related to learners' psychological states. High stress levels negatively affect learning and overall health. Thus, stress-level indicators can be important characteristics of a student's mental health and can help identify learners who require additional support or intervention.

Consequently, these indicators can be used to extract important cross-contextual learner characteristics from trace data, which are important for G&C.

RQ2. Teacher's Feedback about and Evaluations of the characteristics

Interpreting Indicators and Applicability in G&C

Table 2 summarizes the teachers' responses to the multiple-choice items; it shows common answers between the two teachers. Based on the MEXT (2022), the response options for Q1 and Q2 were set as follows.

Q1:

- Possible changes in interest in school and learning
- Possible changes in motivation
- Possible changes in learning methods and strategies
- Possible changes in mental and physical health
- Others

Q2:

- To understand learners' efforts and engagement.
- To identify learners' strengths and provide feedback.
- To encourage learners' self-reflection.
- To provide opportunities for learners' self-determination.
- To praise the student for good behavior and correct undesirable behavior.
- To use as material for discussion in individual meetings with learners.
- To use as material for discussion in parent–teacher meetings.
- Others

The explanatory comments provided alongside these choices were qualitatively coded, and representative excerpts are shown in Table 3. In Table 3, the categories are indicated by the following numbers: (1) subjects of teachers' awareness, (2) situations of use, and (3) teachers' concerns and perceived limitations. Each excerpt was associated with the question in which it was originally expressed, although some comments were relevant to both Q1 and Q2.

Table 2

Interview responses from two teachers

Question	Common Answers
Q1	・Possible changes in interest in school and learning.
	・Possible change in mental and physical health.
Q2	・To understand learners' efforts and engagement.
	・To praise the student for good behavior and correct undesirable behavior.

Table 3

Representative excerpts of coded utterances from teachers

Teacher	Question	Utterance	Code	Category
A	Q1	Changes in home study time, not limited to specific subjects, are beneficial.	Study time data	(1)
B	Q1	Learners need to develop learning habits. It is good that the activity time is visualized, and homeroom teachers can keep track of it.	Study time data, Support for learning habits	(1), (2)
B	Q1	It would be even better if we could see briefly whether learners are achieving the study time you set yourself	Support for Self-determination, limitation	(1), (3)
B	Q1	These can be used as materials for individual meetings with students and parents.	Use in a meeting	(2)
A	Q2	The numbers are not everything, but the stress index needs to be looked at even for children whose numbers are not so high, or at least for those with high numbers; there is a potential for overworking.	Stress-level, Support for lifestyle guidance	(1), (2)
A	Q2	Furthermore, if I had data on sleep duration, I feel like I could immediately apply it to lifestyle guidance.	Support for lifestyle guidance, limitation	(3)

Table 3 represents excerpts of coded utterances from the teachers. From the interview results, teachers found the characteristics valuable for understanding learners' conditions in and out of school, helping to detect changes in interest and mental and physical health, and supporting G&C activities. These include recognizing positive behaviors, addressing undesirable behaviors, and serving as discussion points for learners and their parents. One teacher noted that stress indicators offered insights even for students with low stress and provided opportunities for communication and tailored support.

In contrast, the teachers suggested that a deeper understanding of learners could be achieved by combining additional types of data. For example, one teacher suggested that integrating sleep time data might provide useful guidance for lifestyle management. It is also important to note the kind of learning plans learners set for themselves and the extent to which they achieve them. They expressed interest in utilizing tools that could collect such information and enable its effective visualization and sharing.

In summary, the extracted characteristics aid in understanding learners' learning activities, stressful states, efforts, physical activity, and changes in interest and health.

Benefits of Characteristics from MTSS perspective

Tables 4 and 5 summarize the results of interview question Q3. There were four types of data: ABS in the tables indicates Academic, Behavior, and Social-emotional, respectively.

The number indicates how many of the five teachers answered "useful," and these do not include the number of responses marked as "unclear". In addition, Table 6 presents the coded explanatory comments relevant to Q3. The coding method was the same as that used for Q1 and Q2. Only representative comments were included; specifically, excerpts were selected when three or more teachers made similar remarks.

Table 4

Teacher insights on useful characteristics for tiers and domains

Data	Tier 1			Tier 2			Tier 3		
	A	B	S	A	B	S	A	B	S
(1) Weekly Academic Scores	4	4	2	4	3	0	2	1	0
(2) Learning Activity Time	4	3	2	5	5	2	1	2	1
(3) Steps Taken	1	5	2	2	4	2	0	2	1
(4) Stress Level	4	4	4	3	4	3	2	2	1

Table 5

Teacher insights on characteristics NOT useful for tiers and domains

Data	Tier 1			Tier 2			Tier 3		
	A	B	S	A	B	S	A	B	S
(1) Weekly Academic Scores	0	0	0	0	0	0	0	0	2
(2) Learning Activity Time	0	0	0	0	0	0	1	1	1
(3) Steps Taken	1	0	0	1	0	0	1	1	1
(4) Stress Level	0	0	0	0	0	0	0	0	0

Table 6 Representative coded excerpts from teachers' comments on Q3

Teacher	Utterances	Code	Category
A, B, C, D, E	"Stress levels are useful for every domain." / "Stress affects both academic performance and student behavior." etc	Multi-domain and Tier, Stress-level,	(1), (2)
A, B, C, D	"The score itself is of course important, but it also serves as a clue to grasping the learner's overall academic situation." / "It can also be used for the prevention and early detection of socio-emotional issues," etc.	Multi-domain and Tier, Academic, Support for lifestyle guidance	(1), (2)
A,C,E	"Combining sleep-time data with stress levels may provide deeper insights." / "With sleep duration data, I could immediately apply it to lifestyle guidance." etc.	Sleep-time, Support for lifestyle guidance, limitation,	(2), (3)

The results in Table 4 indicate that teachers are recognizing that one indicator potentially captures more than one domain or tier. For example, the Weekly Academic Score (1) was particularly useful for academics in Tiers 1 and 2, but less so for behavioral and socio-emotional ones. Learning Activity Time (2) was generally useful across all of Tier 2. Step

Taken (3) was helpful for behavioral, but limited in academic and socio-emotional areas. Stress Level (4) was consistently useful across all tiers and was highly valued in the socio-emotional domain. However, all indicators were less effective in capturing Tier 3. In addition, the results in Table 5 suggest that teachers may have difficulty capturing Tier 3 and handling the Steps Taken indicator.

Conversely, on the other hand, the analysis of teachers' explanations revealed that a single indicator may be effective in understanding multiple domains of the MTSS. For example, while all teachers indicated that Weekly Academic Score and study time were mainly useful for understanding the academic domain, some also noted that "the score itself is of course important, but it also serves as a clue to grasping the learner's overall academic situation," and that it "can also be used for the prevention and early detection of socio-emotional issues." Regarding stress levels, teachers commented that they were "useful for everything" and that "it affects both academic performance and student behavior." This code repeatedly appeared in the data, and all five teachers referred to in terms of academic scores, study time, and stress level.

In summary, the findings suggest that while each indicator has varying levels of usefulness across domains and tiers, teachers consistently highlighted the potential of certain indicators to provide broader insights that support both academic guidance and the early detection of socio-emotional issues.

Discussion

In this study, we extracted characteristics from cross-contextual trace data to support teachers' understanding of learners during the G&C process. We aggregated and standardized trace data, transforming it into a level of granularity to enable homeroom teachers to utilize trace data from a G&C perspective. In response to the two research questions, the study identified a set of G&C characteristics derived from trace data and revealed that characteristics can support homeroom teachers in understanding learners' situations both inside and outside of school. In addition, we identified the novelty of this proposal compared to previous studies and recognized its implications in both technological and pedagogical contexts.

Technical Implications

This study extracted characteristics to support teachers' G&C from trace data. This enables teachers to interpret learning and life logs across contexts and understand learners' status in real time. Furthermore, the data utilized in this study supplements the scope achievable with the data currently used in the MTSS model (Felder & Brent, 2005; Saia, 2023). Moreover, this study defines the G&C indicators. These capture learners' favorable and unfavorable states.

Pedagogical Implications

This study provides practical support for teachers involved in G&C by enhancing their understanding of learners and providing supporting interventions. Subjective observations and low-frequency data collected by many teachers often make it difficult to detect learner efforts and may overlook challenges or early signs of change (Wolff et al., 2016; MEXT, 2022). Additionally, the traditional model does not facilitate collaboration and information-sharing with non-teacher stakeholders (e.g., school counselors and social workers) or monitoring behavior following support and intervention (Chapman, 2024).

The systematic approach proposed in this study enhances learner understanding while enabling information sharing and post-intervention monitoring. It has the potential to supplement daily observations and sophisticated screening tests by visualizing potential gaps in teachers' understanding of learners.

Conclusion

Contribution

This study Guidance and Counseling (G&C) using trace data and extracted characteristics for G&C. It explored the potential use of data to support G&C by using trace data stored in the GOAL system to characterize and visualize learner situations through semi-structured interviews with two teachers. The results indicated that the characteristics extracted from the trace data are useful for homeroom teachers to understand the time and effort status of learners' learning activities, stress states, and health statuses. The novelty of this study lies in two key contributions: first, the data aggregation, normalization, and standardization techniques that enable even homeroom teachers—regardless of their subject or specific roles—to interpret and utilize the data effectively; and second, the introduction of objective behavioral log data to support understanding of each tier and domain within the MTSS framework.

Limitations and Future Work

There are three main areas for future research.

The first is the further expansion and integration of the log data. We used log data from the GOAL system, which integrates data from daily activities. However, to use these data for G&C, it is necessary to consider data such as learners' learning logs for many subjects and their lifestyle habits. Furthermore, by integrating diverse data that influence student behavior and outcomes, such as socio-emotional domains and the family environment, it will be possible to analyze learners' situations and to understand them from a multifaceted perspective. In addition, the validity of using stress levels obtained from a single device should also be verified. Moreover, these characteristics only capture the learner's state at a

specific point in time based on the properties of the data and do not focus on the learner's changes over time. Attention to changes in learners is an essential aspect of G&C.

The second limitation was the sample size of the interviewees. Only two teachers were interviewed in the first interview, which served as a needs analysis. In contrast, the second-round interview, which was conducted for evaluation purposes, included five teachers. The sample size should be expanded.

Finally, there was no empirical validation of actual school sites to demonstrate the long-term usefulness of the system. Therefore, the practical effectiveness of the system and its impact on teacher workload and student outcomes require further research and development. Moreover, the effectiveness of the assist Log, a teacher-generated support log that may include, for example, a record of referencing learner characteristics on the dashboard and taking support actions, accordingly, could not be evaluated in this study. However, this may be a promising area for future investigation.

Abbreviations

G&C：Guidance and Counseling; MTSS: Multi-Tiered System of Support; LA: Learning Analytics, RTI: Response to Intervention; SEL: Social and Emotional Learning; LMS: Learning Management System, LEAF: Learning Analytics and Evidence Framework; LRS: Learning Record Store; GOAL: Goal-Oriented Active Learner; SDL: Self-Directed Learning

Author's contributions

JA performed the data analysis and drafted the manuscript. IH, CH and and HO provided insights and reviewed the manuscript. HO acquired funding for the research. The authors read and approved the final manuscript.

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Availability of data and materials

Not applicable.

Declarations

Competing interests

The authors declare that they have no competing interests.

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